Portfolio Construction Using Equity Factors

Executive Summary

The academic research regarding the efficacy of using equity factors, or more specifically, harvesting factor return premiums, is quite extensive. Studies go back several decades.

Our goal with this study is not to expand upon an already vast body of research, but to propose a methodology for constructing a portfolio using factors. In particular, we are testing a thesis that applying a risk budgeting[1] construct to factor exposures can provide alpha versus the S&P 500 Total Return Index with a meaningful degree of confidence.

We begin by examining the historical evidence of factor returns using readily available index data from S&P[2]. We then delve into portfolio analysis using stochastic modeling[3] techniques. In particular, we evaluate the results of various simulations so that we can draw conclusions about our thesis.

While there are numerous methods for portfolio construction, we feel that, based on the results of our modeling, a risk budgeting approach to factor exposures can deliver alpha over extended time horizons. In particular, the results suggest that combining factors can not only deliver alpha, but do so on a compelling risk-adjusted basis.

Factor Performance – Empirical Evidence

For the purposes of this study, we used the total returns of the following U.S. equity factor indexes – 1) S&P 600 Small Capitalization; 2) S&P 500 High Quality; 3) S&P 500 Low Volatility; 4) S&P 500 Enhanced Value and 5) S&P 500 Momentum. While the list above is not exhaustive, we feel it sufficiently covers the U.S. equity universe. The date of our sample corresponds to the common inception period across the underlying indexes, beginning in 2000 and extending through 2018.

Based on historical data over the sample, the factor indexes we selected delivered the following excess returns (Table 1) over the benchmark S&P 500 Total Return Index:

Table 1: Factor Index Excess Annualized Returns (2000-2018)	
S&P 600 Small Cap Index	4.4%
S&P 500 High Quality Index	3.8%
S&P 500 Low Volatility Index	4.9%
S&P 500 Value Index	3.6%
S&P 500 Momentum Index	-0.7%

Note: Excess returns are calculated as the annualized factor index return minus the annualized return for the S&P 500 Index. Source: S&P, Peak Capital Management

Based on the sample, most factor indexes delivered positive (absolute) excess returns over the benchmark. The low volatility factor provided the greatest excess performance, while the momentum factor slightly lagged the broader S&P 500 Index. In particular, momentum suffered substantial drawdowns during the Tech Bubble of the early 2000s, with declines of -20.6% and -26.7% in 2000 and 2001, respectively. The excess return of the momentum factor is roughly 1.3% when excluding 2000 and 2001.

Not only did the factor indexes generally provide positive absolute excess returns, in most cases they also generated superior risk-adjusted performance. Table 2 below provides the Sharpe Ratios for the same indexes from Table 1, as well the S&P 500 Index over the same sample period:

Table 2: Factor Index and S&P 500 Index Sharpe Ratios (2000-2018)	
S&P 600 Small Cap Index	0.5
S&P 500 High Quality Index	0.5
S&P 500 Low Volatility Index	0.7
S&P 500 Value Index	0.4
S&P 500 Momentum Index	0.2
S&P 500 Index	0.3

Note: The Sharpe ratio is calculated by dividing the annualized return for each factor index by the annualized standard deviation of index annual returns. Source: S&P, Peak Capital Management

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Based on historical data, the low volatility factor delivered superior risk-adjusted performance. By mitigating losses in periods like 2000-2002 and 2008, and providing meaningful returns in rising markets, the low volatility factor delivered excess performance with relatively low variation of returns (i.e. a high numerator and low denominator in the Sharpe Ratio calculation).

As mentioned before, the momentum factor delivered a Sharpe Ratio just below the S&P 500 Index, but this was due mainly to the previously mentioned drawdowns in the technology sector in the early 2000s. Excluding the years 2000 and 2001, the Sharpe ratio on the momentum factor increases to 0.5 versus 0.4 for the S&P 500 Index.

One takeaway from historical observations is that excess factor returns are difficult, if not impossible, to predict with any degree of confidence. That is to say, the sequence of year-to-year excess returns is quite volatile, swinging from highly positive (outperform) to deeply negative (underperform).

In Table 3 below, we calculated the standard deviation (tracking error) of annual excess returns for each of the five factor indexes versus the S&P 500 Index over the sample period:

Table 3: Standard Deviation of Annual Excess Returns (2000-2018)	
S&P 600 Small Cap Index	8.7%
S&P 500 High Quality Index	6.7%
S&P 500 Low Volatility Index	10.7%
S&P 500 Value Index	10.3%
S&P 500 Momentum Index	7.1%

Note: The standard deviation of annual excess returns is calculated by taking the standard deviation of the difference between the factor index and S&P 500 Index over the sample period. Source: S&P, Peak Capital Management

To further illustrate how variable factor returns have been historically, we calculated the annual performance of each factor on a calendar year basis in Table 4. Highlighted in green are the top performing factors for each year, while the lowest performing factor is highlighted in red. The historical record indicates that factor return rankings are more-or-less random:

Table 4: Annual Factor Performance

Calendar Year	Size	Quality	Low Volatility	Value	Momentum
2000	11.8%	17.6%	25.0%	19.2%	-20.6%
2001	6.5%	-4.2%	4.4%	14.6%	-26.7%
2002	-14.6%	-14.0%	-7.2%	-22.0%	-16.2%
2003	38.8%	28.7%	22.8%	36.4%	22.5%
2004	22.6%	11.2%	17.7%	20.3%	11.1%
2005	7.7%	5.1%	2.2%	14.6%	16.7%
2006	15.1%	17.6%	19.7%	19.1%	9.6%
2007	-0.3%	15.5%	0.6%	-2.2%	9.9%
2008	-31.1%	-34.1%	-21.4%	-48.2%	-34.6%
2009	25.6%	30.5%	19.2%	35.1%	17.2%
2010	26.3%	15.0%	13.4%	19.2%	18.7%
2011	1.0%	10.9%	14.8%	-2.2%	1.6%
2012	16.3%	14.7%	10.3%	20.7%	17.3%
2013	41.3%	34.2%	23.6%	43.4%	31.4%
2014	5.8%	14.9%	17.5%	11.8%	11.2%
2015	-2.0%	0.4%	4.3%	-5.0%	5.6%
2016	26.6%	9.6%	10.4%	20.4%	5.7%
2017	13.2%	19.5%	17.4%	19.1%	28.3%
2018	-8.5%	-6.8%	0.3%	-9.2%	0.0%

Source: Peak Capital Management

In Table 5 below we segment our sample period into different categories based on bull and bear market characteristics. This table helps identify under what conditions certain factors outperform or underperform on a relative basis:

Table 5: Factor Performance by Market Scenario

Market Scenario[4]	Size	Quality	Low Volatility	Value	Momentum
Jan 00 – Sep 02	-1.1%	-3.7%	6.0%	-0.7%	-22.4%
Oct 02 – Sep 07	18.6%	17.5%	13.4%	19.9%	13.5%
Oct 07 – Feb 09	-39.2%	-32.6%	-25.0%	-53.2%	-31.8%
Mar 09 – Mar 11	47.5%	33.3%	26.1%	56.6%	28.9%
Apr 11 – Nov 11	-7.4%	5.6%	7.3%	-10.9%	-6.0%
Dec 11 – Jan 15	18.1%	19.2%	16.9%	20.4%	18.1%
Feb 15 – Jun 16	5.8%	4.7%	12.6%	0.3%	6.9%
July 16 – Dec 17	22.2%	17.1%	10.0%	28.6%	21.2%
Jan 18 – Mar 18	0.6%	-1.5%	-0.9%	-2.7%	3.4%
Apr 18 – Sep 18	13.9%	11.0%	6.7%	6.3%	15.6%
Oct 18 – Dec 18	-18.6%	-12.7%	-4.7%	-11.1%	-13.9%

Source: S&P, Peak Capital Management

Based on historical data, the low volatility factor tends to outperform on a relative basis during periods when markets are quite turbulent, such as 2008, the drawdown over 2000 through 2002 and the more recent pullback in the fourth quarter of 2018. Likewise, during the recovery years of 2003 through 2007, value stocks outpaced the other factors. The takeaway from Table 5, as with table 4, is that positioning factor exposures based on market environment can be challenging, given the difficulty of timing when we move from one market environment to another.

Conclusions

The empirical data suggests that there is value added by applying factor screens to the U.S. equity market, as evidenced by the excess return figures from Table 1 and the attractive Sharpe Ratios (risk-adjusted performance) from Table 2.

From a portfolio implementation standpoint, however, the standard deviation figures (i.e. the sequence of excess returns) from Table 3, and the randomness of year-to-year factor rankings from Tables 4 and 5, pose a challenge. How do we go about constructing a portfolio of factor-based exposures over longer-term horizons that can potentially provide alpha over the benchmark S&P 500 Index?

In the next section, we provide a basis for allocating across factors using a risk budget methodology. Under this construct, each factor is weighted based on how much risk it presents to the total portfolio on a relative basis (i.e. risk decomposition). While each factor will maintain a positive weight in the portfolio, its exposure is dialed up or down depending on its risk contribution.

Conceptually, this methodology seems rational to us. Avoid making binary in-or-out decisions, because if history is any guide, the timing is difficult and getting it wrong can be costly. Instead, balance the portfolio in such a way as to spread risk equally across the underlying factors, and make allocation adjustments on the margin.

As mentioned before, factors tend to perform differently under various market environments (e.g. recoveries, corrections, recessions, expansions, etc.). The challenge is knowing when we transition from one environment to the next. By managing the risk that each factor presents to the entire portfolio, we can conceivably deliver a sequence of returns that is more favorable than the broader S&P 500 Index, which in turn can lead to more attractive long-term compound performance.

Applying Factor Tilts Through a Risk Budget

To test our thesis that a risk-balanced approach to factor exposures can add value over the S&P 500 Index, we performed a stochastic analysis on the underlying index returns from Table 1 via the bootstrap method. We chose the bootstrap approach to avoid having to make assumptions about future return distributions (i.e. parametric models). By resampling historical data using the bootstrap method, we can capture outliers in the underlying factor indexes and retain a degree of serial correlation in the time series. We then sorted the results of the simulations (e.g. returns, betas, alphas, Sharpe Ratios) into percentiles for analysis.

For the simulation results, we made no assumption about investment expenses, fees, trading costs or taxes.

Simulation Results

Five-Factor Portfolio One-Year Returns

Based on the simulation results, a multi-factor portfolio allocated by equal risk contribution exhibited the following annual return percentiles in Chart 1 below:

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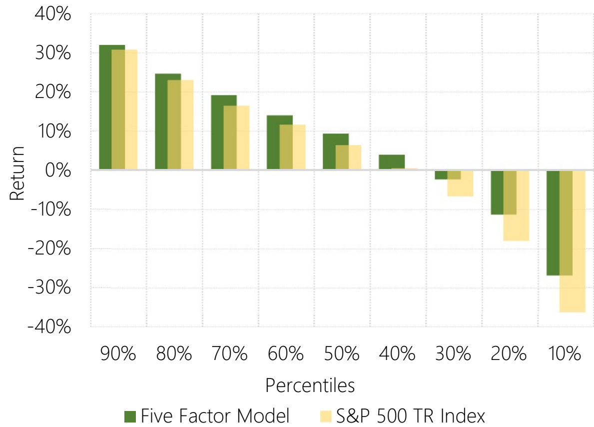
Chart 1: Rolling One-Year Return Percentiles



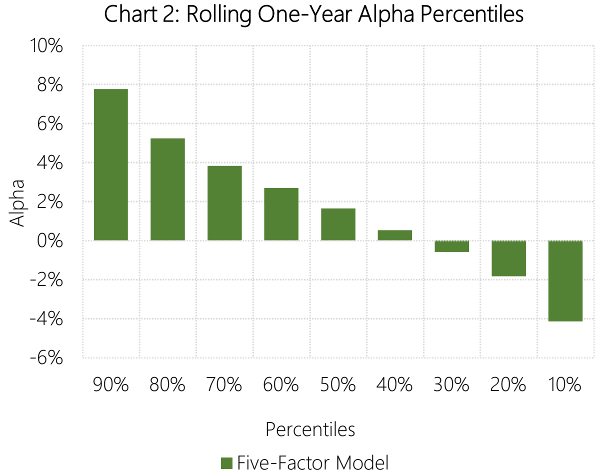
Source: Peak Capital Management

The 50th percentile return over a one-year horizon for the five-factor model was approximately 9%, while the 90th and 10th percentile returns were roughly 32% and -27%, respectively. By comparison, the 50th percentile return for the S&P 500 was approximately 6%, with a range of 31% and -36% at the 90th and 10th percentiles, respectively. These results are expected, given the generally positive alphas across the underlying factor indexes (see Table 1).

Five-Factor Portfolio One-Year Alphas

Based on the simulation results, the five-factor portfolio exhibited the following alpha percentiles versus the S&P 500 in Chart 2 below:

Chart 2: Rolling One-Year Alpha Percentiles



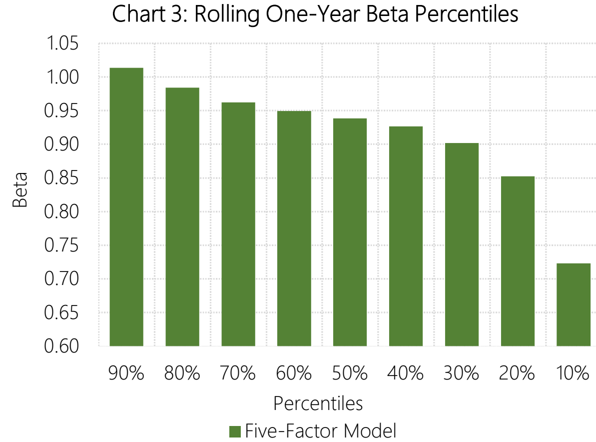
Source: Peak Capital Management

The 50th percentile one-year alpha was roughly 2%, with a range of 8% and -4% at the 90th and 10th percentiles, respectively. In scenarios when a capitalization-weighted index such as the S&P 500 experiences significant downside volatility, factors such as low volatility and high quality can outperform, leading to overall positive alpha for a portfolio weighted by risk contribution. However, when equity returns are driven by a few large-capitalization stocks, an index like the S&P 500 is likely to outperform a factor-based portfolio. Hence, the wide range of alpha over a one-year horizon.

Five-Factor Portfolio One-Year Betas

Based on the simulation, the five-factor portfolio exhibited the following beta percentiles versus the S&P 500 Index in Chart 3 below:

Chart 3: Rolling One-Year Beta Percentiles



Source: Peak Capital Management

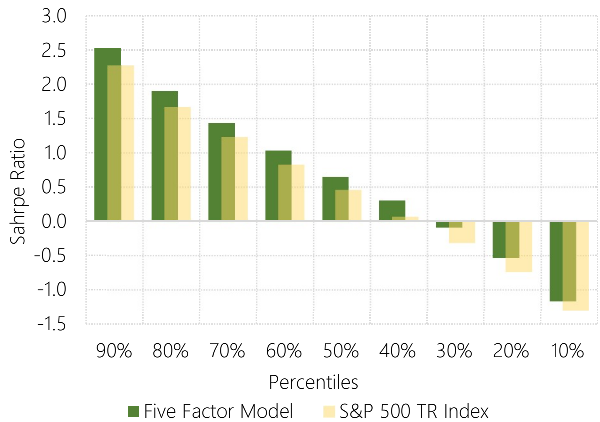
The 50th percentile beta was roughly 0.94, with a range of 1.1 to 0.7 at the 90th and 10th percentiles. As such, the simulated portfolio tended to move in lockstep with the overall S&P 500 Index (i.e. a correlation close to 1) with similar magnitude. Using all five factors in combination provided sufficient coverage of the broad U.S. equity market. This characteristic is noteworthy for clients seeking a core equity portfolio.

Portfolio Construction Using Equity Factors

Five-Factor Portfolio One-Year Sharpe Ratios

Based on the simulation, the five-factor portfolio allocated by equal risk contribution exhibited the following Sharpe Ratio percentiles in Chart 4 below:

Chart 4: Rolling One-Year Sharpe Ratio Percentiles



Source: Peak Capital Management

The 50th percentile Sharpe Ratio for the multi-factor portfolio was approximately 0.7, with a range of 2.5 and -1.2 at the 90th and 10th percentiles. By comparison, the 50th percentile Sharpe Ratio for the S&P 500 Index was roughly 0.5, with a range of 2.3 and -1.3 at the 90th and 10th percentiles.

Five-Factor Portfolio One-Year Allocation Ranges

Based on the simulation, the five-factor portfolio allocated by equal risk contribution exhibited the following asset allocation (factor) ranges in Table 6 below:

Table 6: Multi-Factor Portfolio Allocation Ranges

	Value	Size	Momentum	Quality	Low Volatility
90th Percentile	20%	19%	23%	26%	33%
50th Percentile	16%	16%	18%	22%	27%
10th Percentile	13%	13%	14%	19%	22%

Source: Peak Capital Management

The tilt towards the low volatility factor is expected, given that our methodology is to weight by risk contribution. The allocation ranges vary by roughly 7% to 11% percent. As mentioned before, the portfolio methodology tilts the factor allocations, rather than rotate binarily.

We now extend the simulation over a five-year horizon. The figures that follow are annualized (vs. cumulative). In general, the distribution ranges for the various statistics will narrow between the 90th and 10th percentiles, compared to the shorter one-year analysis.

Five-Factor Portfolio Five-Year Returns

Based on the simulation results, a five-factor portfolio allocated by equal risk contribution exhibited the following annualized return percentiles in Chart 5 below:

Chart 5: Rolling Five-Year Return Percentiles

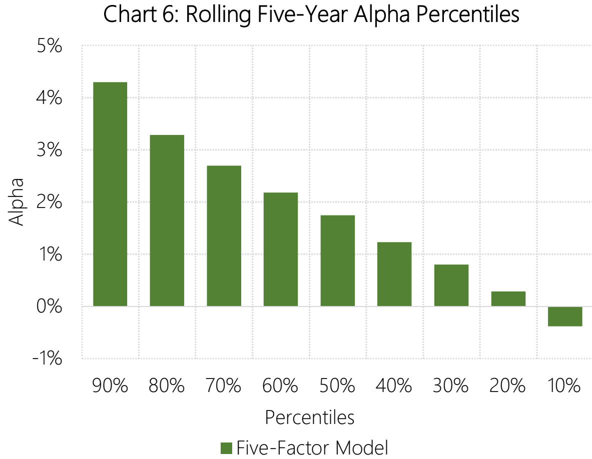
Source: Peak Capital Management

The 50th percentile return over a five-year horizon was approximately 9% (similar to the one-year horizon), while the 90th and 10th percentile returns were roughly 22% and -5%, respectively. By comparison, the 50th percentile return for the S&P 500 was approximately 6%, with a range of 21% and -9% at the 90th and 10th percentiles, respectively. Compared to the one-year analysis, the range of annualized returns for the factor model narrowed over the longer five-hear horizon. A longer investment time frame allows for the recovery of prior losses, which in turn narrows the rage of expected outcomes.

Five-Factor Portfolio Five-Year Alphas

Based on the simulation results, the five-factor portfolio exhibited the following alpha percentiles in Chart 6 below:

Chart 6: Rolling Five-Year Alpha Percentiles



Source: Peak Capital Management

The 50th percentile five-year alpha was roughly 2%, with a range of 4% and 0% at the 90th and 10th percentiles, respectively. The range of alphas narrowed compared to the one-year analysis. The likelihood that a capitalization-weighted index such as the S&P 500 will outperform a multi-factor model diminishes over a five-year horizon. Only at the 10th percentile is the multi-factor model alpha negative (versus the 30th percentile over a one-year horizon).

Five-Factor Portfolio Five-Year Betas

The beta percentiles over the five-year horizon for the factor model are approximately the same as the figures exhibited in Chart 3.

Five-Factor Portfolio Five-Year Sharpe Ratios

Based on the simulation, a five-factor portfolio allocated by equal risk contribution exhibited the following Sharpe Ratio percentiles in Chart 7 below:

Chart 7: Rolling Five-Year Sharpe Ratio Percentiles

Source: Peak Capital Management

The 50th percentile Sharpe Ratio for the factor model was approximately 0.5, with a range of 1.4 and -0.2 at the 90th and 10th percentiles. By comparison, the 50th percentile Sharpe Ratio for the S&P 500 Index was roughly 0.3, with a range of 1.3 and -0.4 at the 90th and 10th percentiles.

Multi-Factor Portfolio Allocation Five-Year Ranges

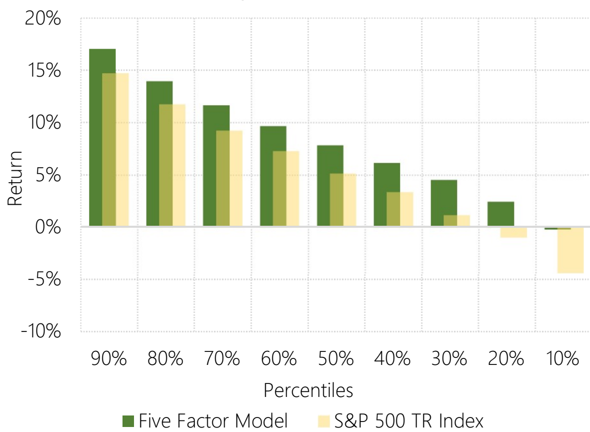
The allocation ranges across the underlying factors over the five-year horizon are essentially the same as the figures provided in Table 6.

Finally, we extend the five-factor model results to a ten-year interval, which generally corresponds to the minimum time horizon for an equity investor. As with the five-year analysis, the figures that follow are annualized.

Five-Factor Portfolio Ten-Year Returns

Based on the simulation results, a five-factor portfolio allocated by equal risk contribution exhibited the following annualized return percentiles in Chart 8 below:

Chart 8: Rolling Ten-Year Return Percentiles



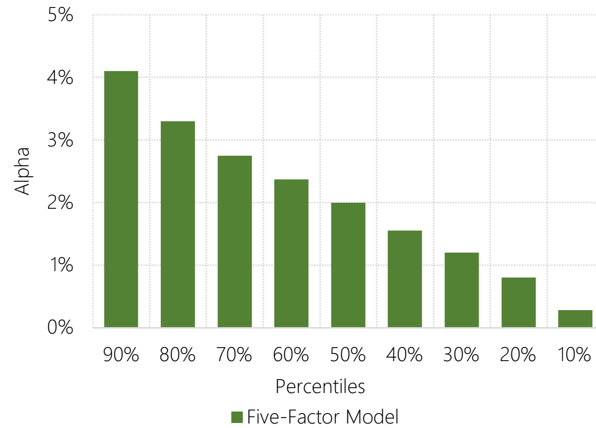
Source: Peak Capital Management

The 50th percentile return for the multi-factor model was roughly 8%, with a range of 17% and 0% across the 90th and 10th percentiles. Likewise, the 50th percentile return for the S&P 500 Index was roughly 5%, with a range of 15% and -4% across the 90th and 10th percentiles. These results suggest a low probability of realizing a negative ten-year rolling return for the multi-factor model.

Five-Factor Portfolio Ten-Year Alphas

Based on the simulation results, the five-factor portfolio exhibited the following alpha percentiles in Chart 9 below:

Chart 9: Rolling Ten-Year Alpha Percentiles



Source: Peak Capital Management

The 50th percentile alpha over ten years versus the S&P 500 Index is roughly 2%, with a range of 4% and 0.3% across the 90th and 10th percentiles. These results suggest that there is a high probability that a multi-factor portfolio will at least match the return of the S&P 500 over a ten-year horizon (i.e. no negative ten-year alpha).

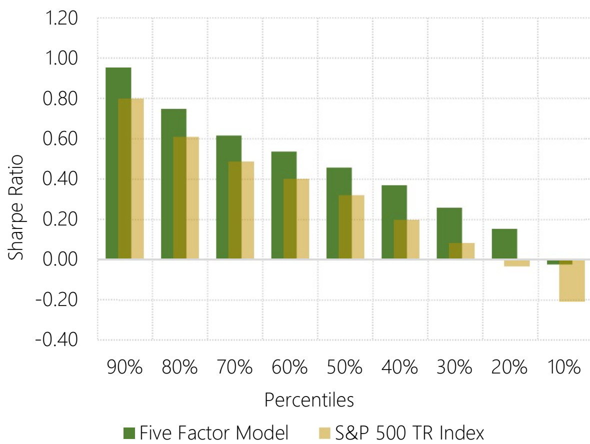
Five-Factor Portfolio Ten-Year Betas

The beta percentiles over the ten-year horizon for the factor model are approximately the same as the figures exhibited in Chart 3.

Five-Factor Portfolio Ten-Year Sharpe Ratios

Based on the simulation, a five-factor portfolio allocated by equal risk contribution exhibited the following Sharpe Ratio percentiles in Chart 10 below:

Chart 10: Rolling Ten-Year Sharpe Ratio Percentiles



Source: Peak Capital Management

At the 50th percentile, the multi-factor model delivered a Sharpe Ratio of roughly 0.5, with a range of 0.9 and -0.02 across the 90th and 10th percentiles. Likewise, the S&P 500 Index produced a Sharpe Ratio of 0.3 at the 50th percentile, with a range of 0.8 and -0.2 across the 90th and 10th percentiles. These results suggest that there is a strong likelihood that a multi-factor equity model will produce superior risk-adjusted performance versus the S&P 500 Index over a ten-year horizon.

Multi-Factor Portfolio Allocation Ten-Year Ranges

The allocation ranges across the underlying factors over the ten-year horizon are essentially the same as the figures provided in Table 6.

Introducing High Beta – The Six-Factor Model

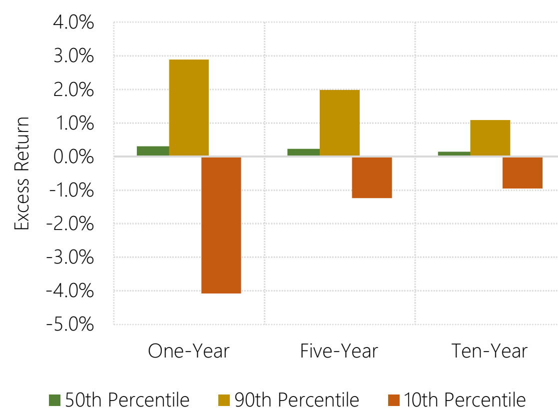
We now extend our original model by including a sixth factor. Specifically, we are testing how adding a high-beta factor impacts the results of the original model. How much does the increased upside potential cost in terms of any increased downside risk?

To model the impact of leverage, we assumed a 2x exposure to the daily return of the S&P 500 Total Return Index (essentially, a high beta factor). The original multi-factor portfolio is expanded to include the leverage factor within the overall risk budget. When S&P 500 volatility is relatively low, the model tends to become more leveraged. That is, the risk budget allows for a greater weight to the leverage factor when volatility decay is not too detrimental. Conversely, when volatility is high, overall leverage is reduced via the risk budget.

Rolling Return Comparison

Based on the simulation results, a multi-factor portfolio allocated by equal risk contribution, including high beta, exhibited the following return percentile distribution in Chart 11 below:

Chart 11: Excess Return of Six Factor Model



Source: Peak Capital Management

The results are derived by comparing the difference between the six-factor and five-factor model returns over multiple time horizons. Based on the results, the 50th percentile returns across all time horizons is essentially the same between the two models. At the one-year horizon, adding a high beta factor increased the 90th percentile return by roughly 3%, but reduced the 10th percentile return by roughly -4%. Hence, for any given year, the marginally higher downside risk outweighs the potential for higher returns. However, when we extend the time horizon, this relationship changes.

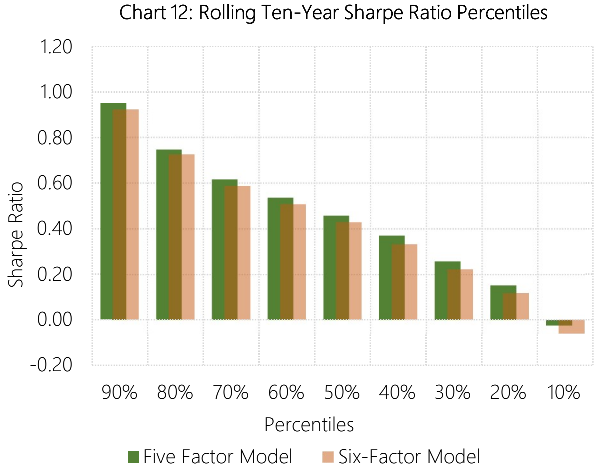
Over a five-year interval, adding the high beta factor increased the 90th percentile return by roughly 2% annualized, but reduced the 10th percentile return by roughly -1.5%. Likewise, over a ten-year interval, the addition of the leverage factor increased the 90th percentile return by just over 1% annualized, while reducing the 10th percentile return by only -0.5%.

The results suggest that over extended time horizons, including a high beta factor can improve expected absolute performance by adding potentially more to the 90th percentile return than what it detracts at the 10th percentile return.

Sharpe Ratio Comparison

Based on the simulation results, a multi-factor portfolio allocated by equal risk contribution, including high beta, exhibited the following Sharpe Ratio distribution over a ten-year horizon in Chart 12 below:

Chart 12: Rolling Ten-Year Sharpe Ratio Percentiles



Source: Peak Capital Management

Based on the results, including the high beta factor did not materially reduce the Sharpe Ratio estimate over a ten-year horizon. For example, the 50th percentile for the six-factor and five-factor models over 10 years is roughly 0.45 and 0.46, respectively. Thus, including the high beta factor seems to potentially increase absolute expected performance over extended horizons without materially diminishing risk-adjusted returns.

Six-Factor Portfolio One-Year Allocation Ranges

Based on the simulation, the multi-factor portfolio with a high beta factor exhibited the following asset allocation ranges shown in Table 7 below:

Table 7: Multi-Factor Portfolio Allocation Ranges

	Value	Size	Momentum	Quality	Low Volatility	Leverage
90th Percentile	18%	16%	20%	21%	28%	12%
50th Percentile	16%	14%	17%	18%	24%	8%
10th Percentile	10%	10%	10%	15%	19%	4%

Source: Peak Capital Management

Based on the percentiles above, the upper end of the leveraged exposure is roughly 12%, or 112% total equity exposure. Likewise, the lower end of the leveraged allocation is approximately 4%, or 104% total equity exposure. Given the addition of the high beta factor, it stands to reason that the overall model beta to the S&P 500 Index is modestly higher than the original five-factor model.

Summary

In this paper, we have illustrated how historically, the use of factors has added long-term value over a passive benchmark like the S&P 500 Index. We've also demonstrated how unpredictable factor return rankings can be over time. From a portfolio implementation standpoint, this uncertainty poses a challenge.

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Our thesis is that a risk budgeting approach, whereby the overall portfolio is equally sensitive to various factor returns, can provide a compelling core equity portfolio. We tested this thesis using stochastic modeling (resampling) of historical returns to develop a level of confidence about our assumptions.

As our paper demonstrates, the results are compelling based on distributions of returns, volatilities, alphas, betas and Sharpe Ratios. In addition, we tested the effect of adding leverage as an additional factor. The result of the analysis was a modest increase in expected return without degrading risk-adjusted performance.

Our conclusion is that a multi-factor portfolio, including leverage, is a suitable investment strategy for clients looking for a core allocation to equities.

This analysis is designed for investors, not traders, and as such, the ten-year time horizon stochastic analysis should be most helpful. Preservation of capital is highly desirable for many investors, particularly when equity markets are experiencing draw downs. The factor-based approach allocated by risk contribution suggests positive gross returns over the ten-year time horizon, even at the 10th percentile.

By reducing portfolio volatility and maximum draw down compared to the benchmark S&P 500 Index, allocating by equity factors should facilitate better investor behavior. Numerous academic studies have demonstrated the panic response by investors during periods of elevated volatility, leading to capitulation at market bottoms.

The methodology for portfolio construction outlined in this paper mitigates specific manager risk that is prevalent in alpha-seeking strategies. Excess returns and attractive Sharpe Ratios are delivered through a disciplined, rules-based process rather than requiring a portfolio manager to make correct macro or individual stock calls. Applying modest leverage can add incrementally higher alpha without materially impacting Sharpe Ratios.

There is no Holy Grail investment strategy, but a methodology able to potentially generate alpha while also delivering attractive Sharpe Ratios should be appealing to institutional investors as well as the investing public.

About The Authors

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Clint Pekrul, CFA is Head of Research at Peak Capital Management (PCM), and is responsible for the development and implementation of the firm's quantitatively driven strategies. Clint has over 16 years of industry experience. Prior to joining PCM, Clint worked in the asset management group at Curian Capital, a registered investment advisor, where he managed $2BB in managed risk strategies. Clint is often heralded as a pioneer in creating and managing portfolios using ETF's. Clint holds a B.S. in business administration from the University of Oklahoma, and is a Chartered Financial Analyst. Clint resides in Denver where he enjoys fly fishing when he is not managing portfolios.

Brian Lockhart, CFP®

Founder & Chief Investment Officer

Brian Lockhart is the founder and Chief Investment Officer of Peak Capital Management, LLC (PCM). With over 20 years of portfolio management experience, he serves as the co-portfolio manager of PCM's suite of strategies. Brian directs the company's dynamic allocation of PCM's unique ETF investment strategies implemented on behalf of high net worth and institutional clients. Brian has been featured in multiple media outlets including Barron's, Forbes, Fortune and Business Week. A graduate of Polytechnic State University in San Luis Obispo, Brian received his Bachelor of Science degree in Business Admin. with a concentration in Financial Management. Brian is also a Harvard alum, having completed an Executive Education course in Investment Decisions and Behavioral Finance at Harvard's John F. Kennedy School of Government in 2017. He and his wife, Cindy, have been married for over 30 years and love living in Colorado where they raised their two children, Caleb and Jennifer.

Disclosures

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This paper uses historical index data provided by a third party. Indexes are not directly investable. The historical performance and simulated returns do not reflect an actual investment strategy or composite. The results shown in this paper are for informational purposes only.

1. Risk budgeting is a portfolio construction methodology whereby the asset allocation is determined by how much risk each holding contributes to the total portfolio. In general, assets are weighted inversely proportional to their price volatility.

2. S&P index data is available at www.spdji.com

3. Stochastic modeling is process used to evaluate market uncertainty. Rather than rely on a single observation, such as historical performance, a stochastic analysis generates a range of possible outcomes, such as best-case and worst-case scenarios. Conclusions can then be drawn based on levels of confidence.

4. Market scenarios are defined as follows: Jan 00 – Sep 02: recession and market correction; Oct 02 – Sep 07: market rally from Sep 02 lows; Oct 07 – Feb 09: global financial crisis; Mar 09 – Mar 11: rally from market lows off the global recession; Apr 11 – Nov 11: European debt crisis; Dec 11 – Jan 15; market rally off the European debt crisis lows; Feb 15 – Jun 16: energy collapse; Jul 16 – Dec 17: market rally; Jan 18 – Mar 18: market pullback; Apr 18 – Sep 18: market rally; Oct 18 – Dec 18: market correction.

Note that the performance figures are hypothetical and do not represent an actual investment track record. The analysis presented is intended to help investors make an informed decision with respect to risk and potential return. The indexes used to generate simulated returns assumes the reinvestment of dividends.

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PCM utilizes standard deviation as a quantification of risk. Standard deviation is a common measure of risk used by academics, analysts, portfolio managers and advisors. The higher the standard deviation the higher the risk. Standard deviation is calculated as the square root of the variance of the data from the average, which is a measure of the dispersion of a set of data from its average. If data points are far from the average, there is a higher deviation within the data set; thus, the more spread out the data, the higher the standard deviation. In finance, standard deviation is applied to the rate of return of an investment to measure the investment's volatility. Standard deviation is also known as historical volatility and is used by investors as a gauge for the amount of expected volatility or the uncertainty of expected returns. Among indexes of stocks, those with smaller companies, international companies and emerging market companies have had higher standard deviations than large companies in the U.S. in long time periods. Among bond indexes, those with longer durations and greater probabilities of default have had higher standard deviations in long time periods. However, it is not true that all indexes with higher standard deviations, such as small growth companies have had higher returns in long time periods. Annualized standard deviation is an approximation obtained by multiplying the monthly standard deviation by the square root of 12, which is 3.46. Please note that the number computed from annual data may differ materially from the estimate obtained from monthly data.

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